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Dynamics of Activation in Semantic and Episodic Memory

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SUMMARY

Spreading-activation models for the structure of semantic and episodic memory postulate a network of interconnected nodes in which activation spreads from a source node to recipient nodes. These models account for a broad range of memory-related processes, including word recognition, sentence verification, prose comprehension, and sentence production. A fundamental question regarding this account concerns the nature of activation growth at each node in the network. Two mutually exclusive possibilities are (a) that activation grows in a discrete fashion, making abrupt transitions between two or more distinct states and (b) that activation grows continuously from a resting level to an asymptotic level. In the present article, we characterize this dichotomy with examples from the literature, and we apply an adaptive priming procedure for testing discrete versus continuous activation models.

Our procedure involves the presentation of prime stimuli at various moments before a test stimulus; subjects are required to make a lexical (word/nonword) decision about the test stimulus. The duration of the interval between the prime and test stimuli is varied adaptively on the basis of subjects' performance. Reaction times are recorded as a function of this duration.

According to discrete activation models, there is a unique reaction-time distribution associated with each possible state of node activation. The distribution of reaction times observed when the test stimulus appears near the moment of transition between discrete states should therefore constitute a finite mixture of the underlying basis distributions associated with the individual discrete activation states. The mixture proportion will depend on the relation between the priming interval and the distribution of state-transition times.

Continuous activation models assert instead that activation grows continuously over time and that there is a unique reaction-time distribution associated with any given degree of intermediate priming. Such models predict that no finite mixture distribution will emerge when the priming interval has a fixed intermediate duration.

Two experiments with the adaptive priming procedure are reported to test these alternative predictions. In Experiment 1, the prime and test stimuli were semantically associated words (e.g., bread–butter). In Experiment 2, episodic associations between the prime and test stimuli were established through paired associate learning. For both cases, the mixture prediction failed, and two-state discrete activation models were rejected.

We conclude that models with only two discrete states of activation, that is, all-or-none models, do not accurately characterize the dynamics of activation in semantic and episodic memory. Higher order discrete or continuous models may better account for the results. Our findings are consistent with several current continuous models of spreading activation. They contrast, however, with those from previous work in which response-preparation processes appeared to proceed in a discrete, all-or-none fashion (Meyer, Yantis, Osman, & Smith, 1985). Apparent differences between the two sets of results and possible theoretical reconciliations are relevant to an overall understanding of interactions between subcomponents of the human information-processing system.

The effects of context upon the speed and accuracy of memory retrieval are well documented in the literature on semantic and episodic memory. Word naming and lexical decisions are facilitated if subjects have first been exposed to other semantically or episodically related verbal material (e.g., Meyer & Schvaneveldt, 1971; Ratcliff & McKoon, 1981; Tulving & Gold, 1963). An important class of models involving spreading activation may account for these context effects and other related phenomena, including letter recognition (McClelland & Rumelhart, 1981), word recognition (Meyer,

Schvaneveldt, & Ruddy, 1975; Morton, 1969), semantic verification (Collins & Loftus, 1975; Collins & Quillian, 1969), sentence comprehension (Anderson, 1976, 1983a, 1983b), concept learning (Ackley, Hinton, & Sejnowski, 1985), associative memory retrieval (Dosher, 1982; Hinton & Anderson, 1981), and sentence production (Dell, 1986).

According to spreading-activation models, human memory incorporates a large number of elementary processing units that are massively interconnected. These units have been variously referred to as nodes, logogens, processors, traces, concepts, and cognitive units, among other terms. We adopt the term *node* here. Associated with each node is an activation value that reflects the current importance, relevance, or availability of the node in memory. Associated with each connection or link between two nodes is a weight reflecting the influence of activation at one of the nodes upon activation at the other. The values of these weights are determined by long-term associative learning and represent the strength of association between the connected nodes.

Spreading-activation models typically embody the following processing assumptions. When one node of a network is activated (e.g., because of information present in the sensory input stream), then activation spreads along the links from this source node to recipient nodes. The spread of activation is modulated by the weights associated with each link. Links between closely associated nodes produce strong and rapid activation of the recipient node. Links between unassociated nodes may produce no activation of the recipient node. Links between mutually inhibitory nodes may suppress activation of the recipient node.

Our goal is to assess the time course of node activation empirically, thereby testing alternative spreading-activation models. In particular, we ask whether activation grows gradually and continuously at each node or undergoes abrupt transitions between discrete activation states. Three distinct classes of spreading-activation models can be identified which differ in the putative time course of node activation. In one class, referred to as *all-or-none models*, there are exactly two discrete states—active or inactive—that a node may occupy over time. In a second class, referred to as *higher order discrete models*, there are three or more finite discrete activation states. The activation functions of these models resemble staircases with as many steps as there are activation states. Finally, in the third class, referred to as *continuous models*, there are no discrete activation states; instead, activation grows gradually with time from an initial resting level to a terminal asymptotic level. In this article, we describe two experiments we have conducted to test these three model classes.

Survey of Activation Models

Here we review a selected subset of the important spreading-activation models that have been developed in the last two decades. We begin with models that postulate discrete, all-or-none activation, proceed to higher order discrete models that assume more than two activation states, and finish with models that assume continuous activation growth over time.

Two-State Discrete Activation Models

According to discrete all-or-none models, nodes can occupy one of only two possible states (e.g., on or off, active or inactive). An early example of such a model was proposed by Quillian (1968; Collins & Quillian, 1969) for sentence verification. It assumed that memory is organized as a hierarchy of concept nodes and that verification is accomplished by placing *activation tags* at the nodes as they are traversed during a search through the network.

Similarly, Anderson (1976) proposed a spreading activation model called ACT in which memory is conceived of as a network of highly interconnected nodes. ACT assumes that each of the nodes occupies an activation state reflecting whether or not the node is currently in working memory. This all-or-none property (Anderson, 1976, p. 123) places the ACT model in the class of two-state discrete models.

Higher Order Discrete Activation Models

According to higher order discrete models, there are more than two possible activation states for the nodes in a network, but the states are nevertheless discrete. A metaphor in which the activation states correspond to semantic features (e.g., Morton, 1969) has been offered to motivate these models. Morton noted that the retrieval of a word from long-term memory may be facilitated when a semantically related word is presented immediately before the retrieval operation. His model for such context effects postulates a number of basic processing units called *logogens*, each corresponding to a stored concept or other semantic entity. Whenever a logogen detects a perceptual or contextual feature to which it is tuned, a counter is incremented. When the counter exceeds a threshold value, the logogen "fires," enabling the response associated with it. Because the logogen model postulates that the activation of each logogen is a feature-counting process, it follows that each logogen can occupy only a finite number of discrete states over time.

There are some other interesting cases of higher order discrete activation models. Link (1975), for example, proposed a random-walk model for simple perceptual decisions. The model hypothesizes a matching process whereby a stim-

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ulus item is compared against an internally represented standard at successive discrete moments of time. During each moment, the difference between the two items is added to an accumulator of discrepancies. If a response threshold is crossed, the associated response is made; otherwise, another discrepancy value is accumulated. This discrete random-walk process can be embedded in a spreading-activation network forming a member of the higher order discrete class.

Continuous Activation Models

In continuous models, the activation value associated with each node in a memory network changes continuously. There is a smooth and gradual growth of activation over time. A metaphor used to characterize such models is that of a liquid moving through a mental "plumbing system."

For example, one influential member of this class, the spreading-activation model of Collins and Loftus (1975), assumes that when a node in a network is stimulated, activation spreads from this source node in parallel along the links of the network to recipient nodes. Activation from various source nodes to a recipient node is summed, and when this sum reaches a threshold, the concept at the recipient node is "evaluated." Further, activation at a node decays gradually over time. The assumption of gradual decay implies that Collins and Loftus (1975) intended to place their model in the continuous class, although it has sometimes been interpreted as belonging to the discrete class (e.g., Dosher, 1982).

There are also several other influential members of the continuous class. Anderson (1983b), in extending his earlier work, proposed a revision of the ACT model, called ACT* (Anderson, 1976). ACT* differs from ACT in that activation is modeled as a continuous rather than a discrete all-or-none process. Ratcliff (1978) proposed a diffusion model of memory retrieval in which each of many memory traces is assumed to be "tuned" to a particular input pattern. When an input pattern is presented as a retrieval cue, activation is accumulated in each of the memory traces in a diffusion process, the continuous analog of a discrete random walk (e.g., Link, 1975).

Among the most well-specified members of the continuous class to date is the interactive-activation model of McClelland and Rumelhart (1981). Like McClelland's (1979) earlier cascade model, it assumes that activation passes between various levels of processing nodes in a negatively accelerated fashion with an exponential approach to asympote. The activation is "interactive" by virtue of feeding simultaneously in a bottom-up manner from low-level to high-level nodes and in a top-down manner from high-level to low-level nodes. This pattern of activation exemplifies the form of processing assumed under what have come to be called connectionist or parallel distributed processing models (Rumelhart & McClelland, 1986), which typically fall into the continuous class, for reasons of both plausibility and mathematical tractability.[1]

Hybrid Models

A fourth class, which we call hybrid models, consists of cases that assume both discrete and continuous modes of activation. One major example of this class has been proposed by Posner and Snyder (1975a). According to their model, there are two kinds of activation in memory, either or both of which may be present under various experimental conditions. The first is automatic pathway activation, which occurs whenever a memory node is activated. Such activation spreads rapidly and continuously from the source node to recipient nodes without awareness, intention, or disruption of other processes. The second kind of activation is controlled, involving all-or-none focusing of attention on a portion of memory as a result of conscious expectancies or strategies. Controlled activation is relatively slow, can be inhibited or halted at will, and generally disrupts other processes. An experiment by Neely (1977) has provided some support for Posner and Snyder's (1975a) model.

Other Models

Several other models of retrieval from memory not reviewed here have also incorporated more or less specific assumptions about activation dynamics. They include examples of discrete (Hayes-Roth, 1977) and continuous (Dosher, 1982; Salasoo, Shiffrin, & Feustel, 1985; Wickelgren, 1976) processing. These examples illustrate the ubiquity of the distinction between discrete and continuous models.

Empirical Approach

Our goal in the remainder of this article is to describe some empirical tests of discrete all-or-none, higher order discrete, and continuous models of activation. Our approach exploits the effects of contextual information in visual word recognition. That word recognition depends on semantic context has been well established. Meyer and Schvaneveldt (1971) first demonstrated the temporal facilitation of a lexical (word–nonword) decision about a test stimulus in the presence of semantically related prime words. Subsequent studies in which a test word was preceded by a related prime word have also revealed reductions of lexical-decision times (e.g., Neely, 1977).

These priming effects may be interpreted in terms of spreading activation in semantic memory. When the prime is presented, its node becomes a source of activation. The activation then spreads to other nodes in its semantic neighborhood, activating them. Less time is thus required to achieve complete node activation (and recognition) for a test word related to the prime than for an unrelated test word, because the activation level of the node corresponding to the related test word is elevated as compared to unrelated nodes.

Following the work of Meyer and Schvaneveldt (1971), interest subsequently developed in the time course of priming effects on word recognition. The time course may be studied by varying the amount of time (stimulus onset asynchrony or SOA) between the onsets of a prime stimulus and a subsequent

[1] Although individual units in some connectionist models take on only discrete (e.g., −1 and 1) values, and computations often take place in discrete time, the global state of most such systems is often best characterized as changing continuously and gradually with time.

test stimulus. These studies demonstrate both a rapid growth of facilitation (i.e., reduced lexical-decision times) with SOA (Antos, 1979; Lorch, 1982; Neely, 1977; Simpson & Burgess, 1985; Warren, 1977) and a gradual decline of facilitation over a period of 4 s or more after prime onset (Meyer, Schvaneveldt, & Ruddy, 1972).

Investigators have frequently interpreted the monotonic changes in facilitation with SOA as indicating that activation grows and decays continuously over time. Mean priming effects are taken as directly reflecting the degree of activation achieved by nodes in memory before the corresponding test words are presented. This interpretation, however, is not the only one possible. Mean priming effects that increase or decrease monotonically with SOA could instead reflect discrete, stochastic activation-state transitions (Dosher, 1982; Meyer & Irwin, 1981; Meyer, Irwin, Osman, & Kounios, 1988). Patterns of mean priming effects thus fail to differentiate definitively between discrete and continuous mechanisms (Kounios, Osman, & Meyer, 1987; Meyer, Yantis, Osman, & Smith, 1985; Wickelgren, 1977).

To overcome this problem, we have used an *adaptive priming procedure* developed by Meyer, Yantis, Osman, and Smith (1984, 1985). The procedure involves providing partial advance information (i.e., a prime) to subjects before the presentation of a test stimulus to which a response must be made. The prime stimulus is typically relevant (beneficial but not essential) to processing the test stimulus. Distributions of reaction times and error rates are analyzed as a function of the prime stimulus and its temporal position relative to the test stimulus. Using this analysis, one can draw inferences about information-processing dynamics associated with recognizing the prime and test stimuli. The procedure is similar in some respects to earlier priming paradigms (e.g., LaBerge, Van Gelder, & Yellott, 1970; Neely, 1977; Posner & Snyder, 1975b; Taylor, 1977); it differs in that more attention is paid here to the quantitative features of reaction-time distributions that underlie the inferences.

Our application of the adaptive priming procedure involves a primed lexical-decision task. In this task, subjects make word–nonword judgments about a letter string on each trial. At various moments before the presentation of the test stimulus, a prime stimulus is presented for a brief period of time (e.g., 0–800 ms). The prime may be semantically related to the test stimulus (if the test is a word) or neutral with respect to the test stimulus. In the present experiments, the neutral prime is "XXXX."

This choice of prime stimuli allows us to collect data under three kinds of priming conditions: unprimed, partially primed, and completely primed. In the *unprimed condition*, the neutral prime is used, yielding no facilitation of performance. The *completely primed condition* involves semantically related or episodically related primes with a long interval between the onsets of the prime and test stimuli (hereafter referred to as the *priming interval*). Here the meaning of the prime can be fully extracted before the test stimulus appears and can thus have its full facilitative effect when the test stimulus appears. The *partially primed condition* involves related primes with medium priming intervals; this condition induces an intermediate mean reaction time.

The partially primed condition, consisting of related primes and medium priming intervals, typically provides the critical results that distinguish the discrete and continuous activation models. If only two discrete activation states occur, and a unique reaction-time distribution is associated with each state, then distributions from the partially primed condition will form a binary mixture of distributions from the completely primed and unprimed conditions, respectively. On the other hand, if activation grows continuously, no such mixture will emerge. These predictions are developed more formally in the next section.

Theoretical Predictions

In this section, we derive predictions from three classes of activation models for data from the adaptive priming procedure. We start by introducing the mathematics of mixture distributions; next we show how the two-state discrete activation models predict that the adaptive priming procedure should yield a family of binary mixture distributions; following that, we describe the predictions for the class of higher order discrete activation models; finally, we describe predictions made by the class of continuous activation models, which do not yield a family of mixture distributions.

Mixture Distributions

Models of the discrete class predict that reaction times from the various priming conditions will form a family of *mixture distributions* having a finite number of underlying bases. As an introduction to mixture distributions, consider the following example. Let $f(x)$ and $g(x)$ be any two nonidentical probability-density functions. Then a third density $h(x)$ is a binary mixture of $f(x)$ and $g(x)$ if it satisfies the following equation:

$$h(x) = \pi f(x) + (1 - \pi) g(x),$$

where π is a *mixture parameter* ($0 \leq \pi \leq 1$). The mixture distribution $h(x)$ may be generated by independently and randomly sampling with probability π from $f(x)$ and with probability $1 - \pi$ from $g(x)$. The functions $f(x)$ and $g(x)$ are the *basis distributions* for the mixture $h(x)$. The binary case is easily generalized to mixtures of k basis distributions. Everitt and Hand (1981) and Smith, Yantis, and Meyer (1988) provide detailed treatments of mixture distributions.

Two-State Discrete Activation Models

The simplest discrete activation models assume two states of node activation: a resting state and an asymptotic state (e.g., Anderson, 1976; Hayes-Roth, 1977; Quillian, 1968). According to these models, the unprimed condition of the adaptive priming procedure will result in the node for the test stimulus occupying its resting state when the test stimulus appears, because the context produced by a neutral prime (e.g., "XXXX") does not change the node's activation level. In the completely primed condition, the test stimulus node will be in its asymptotic activation state when the test stimulus

appears, because the semantic context provided by a related prime would have had its full effect through spreading activation. So the unprimed and completely primed conditions will evidence no priming and full priming, respectively. Associated with each of these two states is a unique basis distribution of reaction times, $f_u(t)$ and $f_c(t)$, respectively.

Now consider what the two-state discrete activation models predict for the partially primed condition. Because there are only two possible activation states, activation from the prime must arrive at the target node and cause a transition from the resting state of activation to the asymptotic state at some moment after prime onset. Assuming that the moment of transition is a random variable (i.e., the transition occurs at different moments from trial to trial due to stochastic noise), then on each trial with a fixed medium priming interval, the node for the test stimulus will be in one of the two activation states when the test stimulus appears. On some trials, this node will occupy the resting activation state when the test stimulus appears, and on others it will occupy the asymptotic state. If, on a given trial, the node happens to be in its resting state when the test stimulus appears, reaction time will be relatively long, as if no prime or a neutral prime had been presented. On the other hand, if the node happens to have achieved its asymptotic state by the time the test stimulus appears, reaction time will be short, as if it had come from the distribution associated with the completely primed condition. According to the two-state models, then, the reaction-time distribution from the partially primed condition should form a binary mixture of the distributions from the unprimed and completely primed conditions, respectively.

The mixture prediction of the two-state discrete activation models is expressed as follows:

$$f_p(t|d) = \pi(d)\, f_c(t) + [1 - \pi(d)]\, f_u(t), \tag{1}$$

where $f_p(t|d)$, $f_c(t)$, and $f_u(t)$ are the reaction-time distributions for the partially primed, completely primed, and unprimed conditions, respectively, $\pi(d)$ is the mixture parameter, and d is the priming interval in the partially primed condition. The value of the mixture parameter $\pi(d)$, and hence of the entire expression, depends on the duration d of the priming interval in the partially primed condition. A relatively short priming interval will result in few trials on which the test stimulus node has achieved full activation by the time the test stimulus appears, whereas a relatively long priming interval will result in many trials on which the node has achieved full activation by the time the test stimulus appears. These two states of affairs correspond to mixture parameters close to zero and one, respectively. Thus, $\pi(d)$ may range from zero to one as d ranges from zero to some extreme positive value that produces essentially complete priming on every trial. In fact, the function $\pi(d)$ is related directly to the distribution function of state-transition times (cf. Meyer et al., 1985, pp. 506–507).

The mixture prediction of the two-state discrete activation models (Equation 1) leads directly to two other equations, which describe the mean $M_p(d)$ and variance $V_p(d)$ of the partially primed density function $f_p(t|d)$:

$$M_p(d) = \pi(d)\, M_c + [1 - \pi(d)]\, M_u, \tag{2}$$

$$V_p(d) = \pi(d)\, V_c + [1 - \pi(d)]\, V_u + \pi(d)\, [1 - \pi(d)][M_u - M_c]^2, \tag{3}$$

where M_c and M_u are the means of $f_c(t)$ and $f_u(t)$, respectively, and V_c and V_u are the corresponding variances. Equation 2 states that the mean of the partially primed distribution will be a linear combination of the means of the completely primed and unprimed distributions. Equation 3 states that the variance of the partially primed distribution will be a function of the mixture parameter $\pi(d)$, the variance of the completely primed and unprimed distributions, and the overall priming effect (i.e., the magnitude of the difference between the means of the unprimed and completely primed distributions). As the overall priming effect increases, the mixture distribution must widen to encompass samples from both of the basis distributions (i.e., $f_c(t)$ and $f_u(t)$). Equation 1 is the strongest prediction of the discrete two-state activation models, and it will be the primary focus of our tests.

Higher Order Discrete Activation Models

Higher order discrete models are also possible (e.g., Link, 1975; Morton, 1969). Such models assert that a unique basis reaction-time distribution is associated with each of k discrete activation states ($k > 2$). This in turn implies that the observed reaction-time distribution for any given medium priming interval will be a mixture of the k basis distributions, as expressed in the following equation:

$$f_p(t|d) = \sum_{i=1}^{k} \pi_i(d)\, f_i(t), \tag{4}$$

where $\pi_i(d)$ and $f_i(t)$ are the mixture parameter and density function, respectively, associated with the ith activation state ($i = 1, 2, \ldots, k$).

Continuous Activation Models

According to the continuous activation models, there is not a finite number of discrete states of activation. Instead, activation grows continuously to some asymptotic value as a function of the priming interval. For example, an exponential priming function may be used to model continuous activation growth (e.g., Anderson, 1983b; McClelland, 1979; Wickelgren, 1977). The following equation, taken from Anderson (1983a), illustrates the growth of activation over time in the ACT* model:

$$a(t) = a_{rest} + [a_{max} - a_{rest}]\, [1 - exp(-ct)],$$

where c is a positive constant. Here activation grows according to an exponential approach to a limit, starting from the resting level at $t = 0$ and reaching a maximum at $t = \infty$.

Given that activation grows continuously, there will be associated with every possible priming interval a distinct reaction-time distribution, the parameters of which will depend on how close activation is to its maximum (Meyer et al., 1985). These distributions will have approximately the same shape and will be approximate translations of one another, with their respective means declining monotonically

to some minimum as the priming interval increases. For present purposes, the important point is that according to a continuous model, observed distributions obtained from the adaptive priming procedure will not constitute mixtures formed from a finite number of underlying basis distributions.

We deliberately avoid providing a further detailed mathematical characterization of the predictions for any individual member of the continuous class. There are several reasons for this. First, many different versions of continuous activation models exist, and we are not concerned with distinguishing them at present. What they all share is the prediction that reaction times will not come from a family of mixture distributions with a finite number of bases. Rather than fitting individual continuous models, we have chosen to discriminate large classes of models (i.e., discrete versus continuous). Second, some continuous models are underspecified with respect to the assumed temporal properties of spreading activation, so one would have to arbitrarily specify how our particular empirical situation would be addressed by these models. For example, consider Ratcliff's (1978) stochastic diffusion model, which has room for multiple interpretations. While the diffusion process is continuous, boundary adjustment within the model could be a discrete process, leading to predictions that are consistent with either the discrete or the continuous class, depending on the specific details of spreading activation one adopts. Finally, because the adaptive priming procedure is specially designed to test for the presence of binary mixture distributions predicted by two-state discrete activation models, the absence of such a mixture would not necessarily have a strong bearing on our evaluation of any particular continuous model.

Overview of Experiments

Our experiments test two-state (all-or-none) discrete models of spreading activation on the one hand versus higher order discrete and continuous models on the other. There are several reasons for this choice of focus. First, models in the two-state class have been especially influential and merit close scrutiny (e.g. Anderson, 1976; Quillian, 1968). Second, it is reasonable for many purposes to treat higher order discrete and continuous models as a single class in contrast to two-state models, because with a moderately large number of activation states, the higher order discrete models can closely mimic properties of the continuous models, whereas the two-state models cannot (Meyer et al., 1985). Third, two-state models are consistent with Sternberg's (1969) additive factor method, which has been enormously influential in cognitive research; it is thus especially important to test these models as a basis for justifying such analytical techniques. Finally, we have empirical procedures that are particularly well suited for assessing the predictions of two-state discrete activation models versus those of higher order discrete and continuous models.

Empirical Assumptions

In order for the proposed analysis of binary reaction-time mixture distributions to correctly diagnose the presence or absence of a two-state discrete activation system, we must assume that the distributions in the three priming conditions (unprimed, partially primed, and completely primed) do not differ in any significant ways other than those perfectly correlated with their respective activation states. If this assumption were violated, then the mixture prediction might be rejected inappropriately. For example, if there are nonspecific preparation or alertness effects (Bertelson, 1967; Posner & Boies, 1971) that vary with the duration of the priming interval, these might dilute the underlying mixture process that generates the data. We have examined the data for this artifact and have been able to rule it out empirically (cf. Results section).

We further assume that the neutral prime ("XXXX") leaves subjects in the unprimed state. This assumption differs from claims made by several investigators, who have suggested that neutral primes consisting of a row of characters (e.g., "XXXX") produce different results than neutral word primes do (e.g., "BLANK" or "READY"; cf. DeGroot, Thomassen, & Hudson, 1982; Jonides & Mack, 1984; Schuberth & Eimas, 1977). In particular, it has been argued that neutral character primes such as "XXXX" yield longer reaction times than neutral word primes do. Consequently, the reaction-time distribution in the present unprimed condition could conceivably be a biased estimate of the "true" unprimed distribution, and the bias could tend to reject the mixture prediction of the two-state discrete activation models (i.e., causing failures of the upper tail in the partially primed distribution to overlap completely with the upper tail in the unprimed distribution). However, the data from Experiments 1 and 2 demonstrate that the mixture prediction is equally misfit in the lower and upper tails of the partially primed and the completely primed distributions. This suggests that our neutral ("XXXX") primes did not result in a spurious rejection of the mixture prediction, and that their use was appropriate.

Finally, it is important that error rates be low and at least approximately equal in absolute magnitude across the various priming conditions, as occurred during our experiments. This requirement follows because the subsequent analyses of reaction-time mixture distributions focus on data from only correct responses. If the error rates were high and differed greatly across conditions, then these differences could bias the resulting estimates of the mixture parameter π away from its true value. It can be shown, however, that such differences would not lead to a spurious rejection of the mixture prediction (Equation 1) made by the two-state discrete activation models. Even with high and variable error rates, the goodness-of-fit tests reported here would still tend to support the mixture prediction if, and only if, it happens to be valid. (Under such circumstances, the true value of the mixture parameter may be recovered by performing analyses on the full complement of reaction-time data, including both correct and incorrect responses in the analyzed distributions.)

Statistical Power

To increase the power of the present tests of the mixture prediction (Equation 1), two aspects of the adaptive priming procedure were carefully controlled. One was the size of the

priming effect, that is, the difference between the means of the reaction-time distributions in the unprimed and completely primed conditions relative to their variances. This difference must be maximized to increase the size of the "inflation factor" in Equation 3.[2] We accomplished the maximization by using prime stimuli that were highly associated with the test stimuli, and by visually degrading the test stimuli (Meyer et al., 1975).

A second aspect of the adaptive priming procedure that may influence the power of the present tests is the value of the mixture parameter, $\pi(d)$. The closer $\pi(d)$ is to 0.5, the larger the variance inflation factor in Equation 3 will be and the greater the statistical power. Thus, to increase power, the reaction-time distribution in the partially primed condition must receive equal contributions from both the unprimed and the completely primed basis distributions. The present experiments were designed to generate a mixture parameter as close to the ideal as possible. We accomplished this by using a staircase tracking algorithm that precisely adjusted the duration of the priming interval, as described later.

Experiment 1

In Experiment 1, we investigated the time course of facilitative priming for retrieval from semantic memory. Subjects made word–nonword judgments about a test stimulus on each trial after seeing a prime stimulus. When the test stimulus was a word, the prime was either neutral ("XXXX") or a close semantic associate of the test stimulus. This let us test whether the semantically associated primes had all-or-none priming effects, as implied by two-state discrete models of spreading activation.

Method

Subjects. Five undergraduate students (3 female, 2 male) served as subjects in four 45-min sessions on successive days. Subjects were paid a base rate of $2.50 per session plus a performance-contingent bonus. They received a total payment of about $4.00 per session.

Apparatus. A Digital Equipment Corporation PDP-11/34 computer controlled data collection. Visual stimuli were displayed on a Hewlett-Packard 2621A display terminal, and responses were made by pressing keys on the terminal's keyboard. Subjects sat in a moderately illuminated sound-attenuating booth.

Stimuli. A list of 288 semantically related word pairs was constructed for the experiments (Yantis, 1985, Appendix A). They were obtained from the association norms of Palermo and Jenkins (1964) and of Bousfield, Cohen, Whitmarsh, and Kincaid (1961). The words had relatively high frequencies (greater than 10 occurrences per million) according to the Kučera and Francis (1967) norms. A list of 288 pronounceable nonwords was also constructed. The nonwords conformed to the orthographic rules of English (Venezky, 1970).

The word and nonword lists served as pools from which prime and test stimuli were chosen. Each subject responded to 180 words and 180 nonwords per day. For each subject on each day, the list of associated word pairs was randomly divided into two 144-pair lists, labeled List A and List B. On each trial, the prime and test stimuli were selected from List A, List B, and/or the list of nonwords, depending on the trial type. When both the prime and test stimuli were words, they were chosen randomly without replacement from among the related pairs in List A. On trials involving a neutral prime and a word test, the test stimulus was chosen randomly without replacement from List B. On trials involving a word prime and a nonword test, the prime was chosen randomly without replacement from List B, and the test stimulus was chosen randomly without replacement from the list of nonwords. Finally, for trials involving a neutral prime and a nonword test, the test stimulus was chosen randomly without replacement from the list of nonwords. For each subject, no test or prime stimulus was displayed more than once per day.

All alphabetic characters were uppercase letters. Each letter subtended a visual angle of about 0.35° in width and 0.5° in height from a viewing distance of 35 cm. The stimuli varied in length from 2 to 9 letters (0.7° to 3.15°).

Design. The design was the same on each of the four days of the experiment. Half of the test stimuli were words, and half were nonwords. One third of the test stimuli were preceded by neutral primes ("XXXX") and the remainder by word primes. Half of the trials for each stimulus type had a long priming interval (700 ms), and the other half a medium priming interval. The experiment was divided into 6 test blocks of 60 trials each, yielding a total of 360 test trials per day. The trials were ordered randomly within each block.

Each type of prime stimulus (neutral or word) was followed equally often by a word or by a nonword test stimulus. Thus, the prime stimulus provided no information about what the next response should be. The prime was only beneficial insofar as subjects could use it to activate nodes in the semantic neighborhood of the prime, thereby facilitating retrieval of the test stimulus when it was a word.

To reduce transient practice effects, certain precautions were taken: (a) each day began with one practice block of 12 trials, (b) every block began with three warmup trials, and (c) every incorrect response was followed by one recovery trial. The responses for all of these filler trial types were discarded.

Procedure. Each trial began with an initial visual warning signal ("####") presented in the center of the display screen for 500 ms, a time chosen to maximize subjects' general level of alertness (Posner & Boies, 1971). Next the prime stimulus was presented for the selected priming interval. Then the prime was replaced by a final warning signal ("—-") for 85 ms. Finally, the test stimulus was presented until the subject made a response. The test stimulus was then extinguished, and a blank 1-s intertrial interval elapsed before the next trial began.

The final warning signal helped attenuate general alertness effects that typically accompany variable foreperiods (Bertelson, 1967). This is important because if a large alertness component contributes to the various reaction-time distributions, then tests of the mixture prediction made by two-state discrete activation models may not be possible.

[2] If a two-state discrete activation process underlies the distribution of reaction times in the partially primed condition, then Equation 3 will hold. Alternately, reaction times from the partially primed condition may have a variance produced by the same mechanism responsible for the variances in the unprimed and completely primed distributions. Our power to test these alternatives is greatest when we create conditions that would yield a partially primed distribution with maximal variance if the mixture hypothesis is correct. Thus, a rough heuristic for gauging the power of the mixture test is that the larger the "inflation factor" $\pi(d)[1 - \pi(d)][M_u - M_c]^2$ in Equation 3, the greater the power. Through a series of stochastic computer simulations, Smith et al. (1988) have shown that a priming effect at least twice as large as the standard deviation of the basis reaction-time distributions from the unprimed and completely primed conditions will usually produce adequate power, given that the number of trials per distribution is not unusually small.

A final warning signal similar to the one used here successfully eliminated alertness effects in studies by Meyer et al. (1985).

To maximize the benefit of the prime in processing the test stimulus, the test stimulus was visually degraded. Meyer et al. (1975) showed that priming effects for degraded test stimuli are significantly larger than those for intact test stimuli. Because subjects presumably try to optimize their performance, they should be more likely to use the prime stimuli under degraded visual test conditions. This is desirable because large priming effects yield greater statistical power in the mixture-distribution tests performed below.

Degradation of each test stimulus was accomplished by alternately flashing the test stimulus and a row of "at" (@) signs, the length of which equaled that of the test stimulus. Each cycle of test stimulus and mask lasted 34 ms. This resulted in the test stimulus being visible but somewhat difficult to see. Despite the difficulty, subjects' error rates suggest that the test stimuli were virtually always resolvable, given enough processing time. The facilitation produced by the semantically related prime stimuli under degraded visual test conditions was substantial. Thus, the use of flicker degradation seems to have been both warranted and effective in the present case.

Responses were made on the terminal keyboard with the right and left index fingers. If the test stimulus was a word, the slash key (/) was pressed with the right index finger; if it was a nonword, the *Z* key was pressed with the left index finger. A point system was used to motivate fast but highly accurate responding (Pachella, 1974). Bonus points, convertible into small cash payments, were awarded for fast and accurate responses, with accuracy stressed.

Feedback was provided after each trial of the initial practice block on each day, giving the reaction time and bonus points earned for that trial (on correct responses) or the message "error—lose 300 points" (if an error was made). On subsequent test blocks, there was no feedback after correct responses; the word "error" appeared for 500 ms after errors. At the end of every block, a summary feedback chart was displayed showing the number of correct and incorrect responses, average RT, and bonus points earned for the block and cumulatively for the session.

Priming intervals. The long priming interval was set at 615 ms (which, when added to the 85-ms final warning signal, yielded a priming interval of 700 ms). This allowed enough time for virtually complete processing of the prime stimuli (Meyer et al., 1985). The medium priming interval was adjusted adaptively with a staircase tracking algorithm for each subject on a trial-by-trial basis. Our objective here was to place the median of the partially primed reaction-time distribution midway between the medians of the unprimed and completely primed distributions. This maximized the power of subsequent statistical tests by ensuring that the partially primed condition yielded reaction times approximately intermediate between those from the unprimed and completely primed conditions.

The tracking algorithm used methods developed in sensory psychophysics to study psychometric functions (Levitt, 1971). The details of this algorithm and its properties may be found in Meyer et al. (1985, Appendix C). The adjustment of the medium priming interval was designed to converge on an ideal value; after Day 1, the duration of the medium priming interval remained quite stable.[3]

Data analysis. The ultimate goal of the adaptive priming procedure is to test the binary mixture prediction of the two-state discrete activation models. To achieve this goal, we used a maximum-likelihood goodness-of-fit test (Smith et al., 1988). The test iteratively estimated mixture parameters and basis distributions that came closest to the data while conforming to a perfect binary mixture (Equation 1). The result of the fitting procedure is a maximum-likelihood goodness-of-fit statistic, a best-fitting set of basis distributions for the unprimed and completely primed conditions, and a vector of mixture parameters. To the extent that the data conform to a perfect mixture, the goodness-of-fit statistic will have an approximate chi-square distribution with degrees of freedom depending on the number of bins per basis distribution. If the goodness-of-fit statistic falls outside conventional limits of significance (in this article, $\alpha = .05$), the mixture prediction must be rejected, and models making that prediction must be altered or discarded. For further details about the fitting procedure, see Meyer et al. (1985) and Smith et al. (1988).

Results

For the response statistics and mixture analyses reported below, only correct responses were used. We report in detail the response statistics from Day 3 of the experiment. The data from Days 2 and 4 were completely consistent with those from Day 3. The priming effects and goodness-of-fit tests are reported for all three days. Day 1 was considered practice, and Day 1 results are not reported.

Response statistics. Table 1 lists response statistics separately for each subject as a function of condition on Day 3. Figure 1 depicts the data graphically for each subject separately on Day 3, showing mean reaction time as a function of priming condition and test stimulus type. Each panel of the figure corresponds to one subject.

Several features of these data are of interest. First, as in typical lexical-decision studies (e.g., Meyer et al., 1975), subjects took longer to decide that a test stimulus was a nonword than to decide that it was a word. Second, error rates were low, averaging 4.8% over subjects and conditions on Day 3 and 4.2% over Days 2–4. High error rates tended to be associated with long reaction times ($r = .28$); a strong speed–accuracy trade-off did not occur. Third, mean reaction times generally decreased as the priming interval increased.

Table 2 lists the priming effects for responses to word and nonword test stimuli as a function of priming interval. Each integer in the table is the difference (in milliseconds) between the mean reaction time obtained with related prime stimuli and that obtained with neutral prime stimuli for the indicated priming interval. Priming effects were uniformly larger under the long priming interval than under the medium priming interval. The mean priming effects across subjects were substantial. These large priming effects replicate earlier work showing significant improvements in lexical-decision times as the priming interval increases (e.g., Neely, 1977). In agreement with the priming effects on reaction times, error rates also decreased as the priming interval increased.

The staircase tracking algorithm was effective in selecting a medium priming interval such that the partially primed distribution of reaction times fell midway between the unprimed and completely primed (basis) distributions. When we divided the priming effect in the partially primed condition by the priming effect in the completely primed condition, we typi-

[3] Stability of the priming interval in the partially primed condition is important because large variation in this interval across trials could produce spurious extra variance in the partially primed distribution, increasing the probability of accepting the mixture hypothesis. However, because the mixture hypothesis was rejected in the present case, this potential difficulty is less problematic.

Table 1
Results From Individual Subjects on Day 3 of Experiment 1

Priming condition	Mean RT (ms)	SD (ms)	Errors (%)
	Subject G.S.		
Word			
Unprimed	511	62	1.7
Partial	452	43	0.0
Complete	373	133	1.7
Nonword			
Unprimed	533	60	0.0
Partial	517	74	0.0
Complete	484	114	0.0
	Subject N.A.		
Word			
Unprimed	563	95	13.3
Partial	450	68	3.3
Complete	345	126	3.3
Nonword			
Unprimed	559	96	5.0
Partial	576	87	6.7
Complete	505	76	5.0
	Subject P.B.		
Word			
Unprimed	554	85	3.3
Partial	477	57	0.0
Complete	419	85	1.7
Nonword			
Unprimed	599	65	3.4
Partial	566	43	1.7
Complete	527	67	1.7
	Subject L.P.		
Word			
Unprimed	527	68	20.0
Partial	454	44	3.3
Complete	396	78	6.7
Nonword			
Unprimed	520	59	18.3
Partial	540	49	6.7
Complete	491	60	8.3
	Subject S.R.		
Word			
Unprimed	558	60	3.3
Partial	484	39	0.0
Complete	467	78	1.7
Nonword			
Unprimed	593	87	3.3
Partial	616	67	13.3
Complete	534	58	6.8

cally obtained values close to 0.5 (see the columns headed "*Priming ratio*" in Table 2). If the tracking algorithm had worked perfectly, these values would have equaled exactly 0.5. Of the fifteen values for word test stimuli listed in Table 2, eight (all on Days 3 and 4) are between 0.4 and 0.6.

Tests for binary mixture distributions. Table 3 shows the results of our maximum-likelihood goodness-of-fit tests for the binary mixture distributions predicted by the two-state discrete activation models (Smith et al., 1988). These models are not supported. Results of 15 such tests involving word test stimuli (5 subjects in three sessions each) may be summarized very concisely. When the test stimulus was a word, the binary mixture prediction was clearly rejected in 14 of the 15 cases. On Days 3 and 4, the goodness-of-fit statistic was always highly significant, with χ^2 values at least three times and as much as eight times the degrees of freedom, and p values always less than 0.001. These significant deviations indicate that the reaction-time distributions from the partially primed condition were not simply discrete binary mixtures of those from the completely primed and unprimed conditions, contrary to the two-state discrete activation models.

Figure 2 shows reaction-time frequency distributions produced by one representative subject (P.B.) on Day 3 of Experiment 1 for word stimuli. The upper, middle, and lower panels correspond to the unprimed, partially primed, and completely primed conditions, respectively. The solid lines represent observed frequencies and the dashed lines represent the best fitting binary mixture distributions. The goodness-of-fit statistic for these data is highly significant, $\chi^2(8) = 48.8$, p

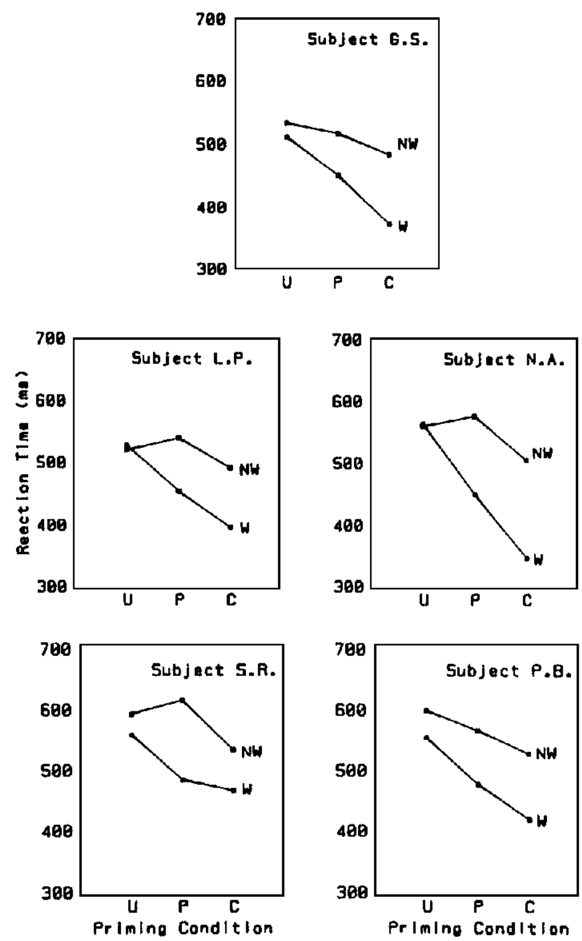

Figure 1. Mean reaction time as a function of priming condition and type of test stimulus for each subject on Day 3 of Experiment 1. (U = unprimed condition; P = partially primed condition; C = completely primed condition; W = word test stimuli; NW = nonword test stimuli.)

Table 2
Priming Effects (in Milliseconds) for Individual Subjects as a Function of Priming Interval: Experiment 1

	Test stimulus					
	Word			Nonword		
	Priming effects			Priming effects		
Day	Medium interval	Long interval	Priming ratio	Medium interval	Long interval	Priming ratio
	Subject G.S.					
2	47	70	.67	9	20	.45
3	59	138	.43	16	49	.33
4	67	205	.33	47	141	.33
	Subject N.A.					
2	85	104	.82	−11	24	—
3	113	218	.52	−17	54	—
4	139	319	.44	−10	88	—
	Subject P.B.					
2	60	94	.64	35	52	.67
3	77	135	.57	33	72	.46
4	80	143	.56	48	89	.54
	Subject L.P.					
2	90	96	.94	22	50	.44
3	73	131	.56	−20	29	—
4	78	155	.50	5	55	.09
	Subject S.R.					
2	51	66	.77	−8	47	—
3	74	91	.81	−23	59	—
4	84	143	.59	−10	86	—
M	78	141	.55	8	61	.13

Note. Priming ratio is equal to priming effect under the medium priming interval divided by priming effect under the long priming interval.

$< .001$, indicating a very poor fit for the mixture prediction of the two-state discrete activation models.

The pattern shown in Figure 2 typifies the manner in which the mixture prediction failed for all subjects: The lower tail of the partially primed distribution does not overlap with the lower tail of the completely primed distribution, and the upper tail of the partially primed distribution does not overlap with the upper tail of the unprimed distribution. Significant portions of the two putative basis (i.e., unprimed and completely primed) distributions made no contribution to the putative mixture (i.e., partially primed) distribution. The prediction from the class of two-state discrete activation models that a family of binary mixture distributions will arise from the adaptive priming procedure is clearly disconfirmed for semantic-context effects in lexical-memory retrieval.

Two additional features of the data deserve comment. First, the mixture parameter π estimated in each test has no clear-cut interpretation when the mixture prediction is violated, as it has been here. The estimates are provided in Table 3 only for completeness. Second, because the tests for the nonword stimuli lacked power, these tests are not discussed further. Indeed, when the mean of the partially primed reaction-time distribution does not fall between the means of the unprimed and the completely primed distributions, as it sometimes did here for nonwords in violation of Equation 2, the application of mixture tests is not justified.

Paralleling the distributional analyses, the variance of the partially primed distribution was not larger than the variance of the unprimed and completely primed distributions. According to Equation 3, the variance of the partially primed distribution should exceed those of the unprimed and completely primed distributions if the priming effect is substantial and the mixture parameter is close to 0.5, as they were here. However, the variance of the partially primed distribution did not exceed that of either basis distribution for any subject (Table 1). Instead, in many cases, the variance of the partially primed distribution was actually *smaller* than those of both basis distributions.

Neutral primes. Experiment 1 also included a control manipulation involving the two priming intervals for the neutral prime stimuli. On half of the trials when the prime stimulus was neutral ("XXXX"), the priming interval was long, and on the other half, the priming interval had the current medium duration. These conditions index the extent to which alertness effects (e.g., Bertelson, 1967; Posner & Boies, 1971) were attenuated by the final warning signal. Because there was no specific information available from the neutral primes, differences in reaction time produced by them for the two

Table 3
Goodness-of-Fit Tests for the Mixture Prediction of the Two-State Discrete Activation Models in Experiment 1 on the Basis of Responses to Word Test Stimuli

Day	Mixture parameter (π)	χ^2 (8)
	Subject G.S.	
2	.44	18.8*
3	.63	35.0***
4	.33	42.9***
	Subject N.A.	
2	0.0	28.8***
3	0.0	65.8***
4	1.0	62.9***
	Subject P.B.	
2	.58	20.2**
3	.21	48.8***
4	.44	56.8***
	Subject L.P.	
2	1.0	12.0
3	.87	33.8***
4	.98	43.6***
	Subject S.R.	
2	.95	14.4*
3	1.0	29.1***
4	.97	34.8***

* $p < .05$. ** $p < .01$. *** $p < .001$.

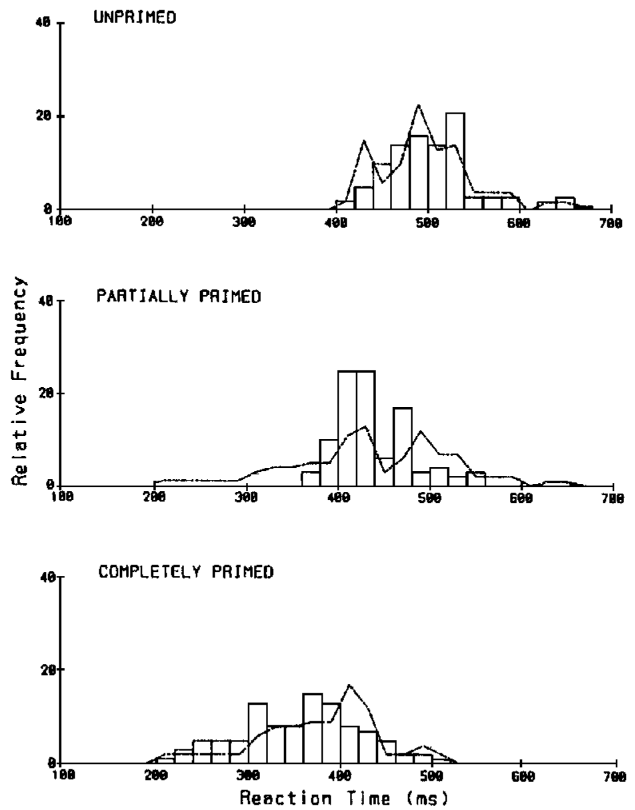

Figure 2. Results from Subject P.B. on Day 3 of Experiment 1, when the test stimuli were words. (The upper, middle, and lower panels correspond to the unprimed, partially primed, and completely primed conditions, respectively. The solid lines in each panel represent data frequencies and the dashed lines the best-fitting mixture distributions.)

priming intervals would indicate the presence of nonspecific alertness effects.

The mean reaction times obtained with the neutral primes are listed in Table 4 separately for each subject on Day 3. Under the medium and long priming intervals, collapsed across subjects and Days 2–4, the means were 536 and 551 ms, respectively. This difference of 15 ms was significantly different from zero, $t(14) = 2.3$, $p < .05$; however, it was small in absolute magnitude and went in the opposite direction from what would ordinarily be expected with informative primes or effects due to changes in nonspecific alertness. Thus, nonspecific alertness does not appear to account for or contribute to performance observed here with informative primes as a function of the priming interval. The final warning signal evidently eliminated the alertness effects that are often observed in preparation studies. This fact justifies combining responses from the two neutral-prime conditions into a single unprimed distribution for purposes of the mixture tests reported earlier.

Table 4
Mean Reaction Times (RT; in Milliseconds) Obtained With Neutral Primes for Word Test Stimuli as a Function of Priming Interval on Day 3 of Experiment 1

	Mean RT		
Subject	Medium interval	Long interval	RT difference
G.S.	498	525	27
N.A.	560	566	6
P.B.	539	570	31
L.P.	522	532	10
S.R.	561	554	−7
M	536	549	13

Discussion

Experiment 1 demonstrates that two-state discrete models of activation in semantic memory are untenable under the present conditions (i.e., when the test stimuli are semantically related to the prime stimuli). In the partially primed condition, reaction times did not come from a binary mixture of those obtained under the unprimed and completely primed conditions. Models asserting that nodes in memory occupy only two states (i.e., activated or unactivated) cannot account for this result. For example, we may now reject Quillian's (1968) original spreading-activation model, Anderson's (1976) ACT model, and Hayes-Roth's (1977) retrieval model, which all postulated just two activation states.

On the other hand, continuous models of spreading activation are consistent with the results of Experiment 1. These models, as outlined earlier, imply that there is a unique reaction-time distribution associated with any given degree of intermediate priming. The distribution in the partially primed condition should therefore be roughly a translation of the distributions from the unprimed and the completely primed conditions. The present results support such models. For example, the interactive-activation model of McClelland and Rumelhart (1981), Anderson's (1983b) ACT* model, and Ratcliff's (1978) diffusion model (among others) are supported by our results

We do not yet wish to conclude, however, that memory activation is always continuous. A limitation of Experiment 1 is that it involved words with strong preestablished associations, which may have induced massive automatic spreading activation (Neely, 1977; Posner & Snyder, 1975a). Perhaps such activation involves a continuous growth process, whereas controlled nonautomatic memory retrieval involves an all-or-none activation process. If so, we would expect that a priming procedure employing episodic relations between the prime and test stimuli might produce a family of binary mixture distributions as in Equation 1, supporting the two-state discrete activation models, even though the results of Experiment 1 did not. Experiment 2 was designed to test this hypothesis.

Experiment 2

In Experiment 2, we tested the mixture prediction of the two-state discrete activation models under conditions meant to produce strategic or "controlled" retrieval of episodic,

rather than semantic, information from memory. Episodic relations between semantically unrelated prime and test stimuli were established in a preliminary paired-associate learning task. These relations then served as the basis for the prime-test pairs in the adaptive priming procedure. It seemed likely that this would still yield reasonably large priming effects, even though the nature of the activation process (all-or-none vs. higher order discrete or continuous) might change from what was observed in Experiment 1. Using a procedure in some ways similar to ours, McKoon and Ratcliff (1979) found equally large priming effects when the prime and test stimuli were related episodically through a paired-associate learning task and when they were semantically related. The present study extends their work by examining the dynamics of the activation process that mediates episodic priming.

Method

Subjects. Six University of Michigan undergraduates were paid to participate as subjects in three 50-min sessions.

Apparatus. The equipment was the same as in Experiment 1.

Stimuli. Forty common adjectives were used as prime and test words. Separately for each subject, the adjectives were randomly divided in half, with one set serving as primes and the other as test words. The particular prime-test pairings were also chosen randomly, yielding one list of 20 paired associates per subject. These lists of pairs, once constructed (one unique set of pairings per subject), remained constant. Over the course of each session, subjects saw each pair repeatedly. Nonwords were chosen randomly from the list of 288 nonwords constructed for Experiment 1.

Design. The experiment had two main parts. In the first part, conducted on Day 1, subjects learned their list of 20 paired associates via an anticipation method to a criterion of three cycles through the list without error. This was followed, also on Day 1, with 180 trials of practice on the adaptive priming procedure, using the prime-test pairs just learned.

The design of the adaptive priming procedure was similar to that of Experiment 1. Half of the test stimuli were words and half nonwords; 40% of the primes were neutral ("XXXX") and the rest were words. Half of the trials for each stimulus type had a medium priming interval, and the rest had a long priming interval. Whenever both the prime and test stimuli were words, they had been paired in the initial paired-associate learning task. Any given prime was followed equally often by a word and by a nonword, so the identity of the prime contained no information about the response that would be required. However, the primes were useful insofar as they activated representations of the associated test words.

There were 60 trials per block. Three blocks were run as practice on Day 1 after the paired-associate learning task; on Days 2 and 3, eight blocks were run, yielding a total of 480 trials per day. As in Experiment 1, Days 2 and 3 began with a short practice block of 20 trials, each block began with three warmup trials, and each error was followed by a recovery trial. The responses for each of these trial types were discarded.

Paired-associate learning task. During the paired-associate learning task, which established the desired episodic relations between the prime and test words, subjects were told to look at the first member of each selected word pair (20 pairs in all) and to recall the second member of the pair. Each trial proceeded as follows. The first word of a pair was displayed slightly to the left of center on the screen for 2 s. Next, a dash appeared for 500 ms slightly to the right of the first word (which remained on the screen). The dash was a cue that a response or guess should be made, because the second member of the pair was imminent. Subjects responded, if possible, by speaking aloud the remembered associate of the first word. The second member of the pair (i.e., the correct response) then appeared slightly to the right of the dash for 2 s, after which the screen was erased. The next trial began 1 s later. The experimenter sat in the booth and recorded the accuracy of each response. Responses had to be made within the 2.5-s duration of the first word, but were not otherwise speeded. The order of presentation of the 20 pairs was random in each learning block.

On each day, the paired-associate learning task was repeated in blocks of 20 trials until every response was correct for three cycles through the list. The number of blocks to reach criterion ranged from 10 to 19 on Day 1. On Days 2 and 3, subjects took no more than 5 blocks to reach criterion, and in those cases involving more than the minimum of 3 blocks, an error in only one response was responsible for less than perfect performance.

Lexical-decision task. The lexical-decision task for the adaptive priming procedure was conducted in exactly the same manner as in Experiment 1. The only difference between the two experiments involved the ensemble of prime and test stimuli.

Results

Response statistics. The priming data from Days 2 and 3 were analyzed as before. The data from Day 1, involving only 180 trials of practice, were not analyzed. Only data based on correct responses are included in the reaction-time statistics and the mixture tests reported below.

Table 5 shows the response statistics and Table 6 the priming effects on Day 3 for each subject. Figure 3 illustrates the mean reaction times for each subject separately on Day 3 as a function of the prime-test relation and priming condition. Error rates on Day 3 were low overall, averaging 3.6% over subjects and conditions. The correlation between reaction times and error rates was 0.29, indicating that subjects did not engage in a strong speed–accuracy trade-off.

As in McKoon and Ratcliff (1979), substantial priming effects emerged from the episodic relations introduced between the words paired during the initial paired-associates learning task. For every subject, reaction times obtained with related primes were substantially less than those obtained with neutral primes when the test stimuli were words. This result is illustrated in Table 6, which shows the difference in mean reaction times induced by the related and neutral primes as a function of the priming interval (medium vs. long) for Day 3.

For word test stimuli, the priming effect averaged 60 ms with the medium priming interval and 98 ms with the long priming interval. The staircase tracking algorithm was fairly effective in placing the reaction-time distributions in the partially primed condition midway between those in the unprimed and the completely primed conditions, with an overall priming ratio of .61, and with 6 of the 12 priming ratios between .4 and .6. This outcome, combined with the large episodic priming effects, helps ensure that our tests of the binary mixture prediction made by the two-state discrete activation models were reasonably powerful.

Tests for mixture distributions. As in Experiment 1, the obtained distributions of reaction times from the partially primed conditions violated the mixture prediction made by

Table 5
Results From Individual Subjects on Day 3 of Experiment 2

Priming condition	Mean RT (ms)	SD (ms)	Errors (%)
	Subject M.D.		
Word			
Unprimed	497	56	10.5
Partial	453	59	2.8
Complete	417	64	5.6
Nonword			
Unprimed	498	49	3.1
Partial	464	49	4.2
Complete	421	55	1.4
	Subject A.A.		
Word			
Unprimed	511	57	2.1
Partial	457	75	1.4
Complete	418	55	0.0
Nonword			
Unprimed	536	66	0.0
Partial	527	43	2.8
Complete	468	44	2.8
	Subject L.G.		
Word			
Unprimed	534	48	6.3
Partial	423	35	0.0
Complete	408	63	5.6
Nonword			
Unprimed	487	48	1.0
Partial	498	56	5.6
Complete	432	54	1.4
	Subject R.D.		
Word			
Unprimed	541	69	4.2
Partial	478	72	2.8
Complete	408	65	2.8
Nonword			
Unprimed	583	60	4.2
Partial	558	50	5.6
Complete	509	70	4.2
	Subject K.H.		
Word			
Unprimed	514	57	4.2
Partial	457	65	1.4
Complete	435	65	2.8
Nonword			
Unprimed	553	54	0.0
Partial	538	52	4.2
Complete	465	53	0.0
	Subject M.C.		
Word			
Unprimed	549	63	3.2
Partial	486	52	2.8
Complete	443	56	5.6
Nonword			
Unprimed	563	84	5.2
Partial	526	70	1.4
Complete	486	59	1.4

Table 6
Priming Effects (in Milliseconds) for Individual Subjects as a Function of Priming Interval: Experiment 2 (Days 2–3)

	Test stimulus					
	Word			Nonword		
	Priming effects			Priming effects		
Day	Medium interval	Long interval	Priming ratio	Medium interval	Long interval	Priming ratio
			Subject M.D.			
2	48	60	.80	28	72	.39
3	44	80	.55	34	77	.44
			Subject A.A.			
2	50	128	.39	−20	66	—
3	54	93	.58	9	68	.13
			Subject L.G.			
2	89	119	.75	−21	37	—
3	61	76	.80	−11	55	—
			Subject R.D.			
2	52	102	.51	0	64	0.0
3	63	133	.47	25	74	.34
			Subject K.H.			
2	65	113	.57	8	89	.09
3	57	79	.72	15	88	.17
			Subject M.C.			
2	73	86	.85	−8	66	—
3	63	106	.59	37	77	.48
M	60	98	.61	8	69	.12

Note. Priming ratio is equal to priming effect under the medium priming interval divided by priming effect under the long priming interval.

the two-state discrete activation models (Table 7). Significant deviations emerged in 10 of 12 goodness-of-fit tests performed on the data for Days 2 and 3. The nature of the deviations paralleled those found previously in Experiment 1: in most cases, the distribution from the partially primed condition fell neatly between those from the unprimed and completely primed conditions, and it did not contain significant contributions from the tails of either of those basis distributions.

Note also that as in Experiment 1, the magnitudes of the standard deviations under the partially primed conditions were not consistently larger than those under the unprimed and completely primed conditions, as predicted by Equation 3 (cf. Table 5). Once again, from the perspective of variance, the mixture prediction did not hold up well.

Neutral primes. The mean reaction times induced by the neutral primes were 523.3 ms and 522.8 ms, respectively, following the medium and long priming intervals, $t(17) = 0.2$. As intended, the final warning signal greatly attenuated the nonspecific alerting effects frequently observed when foreperiods are varied (Bertelson, 1967). Thus, the present priming effects obtained with episodically related primes cannot simply be attributed to changes in nonspecific alertness.

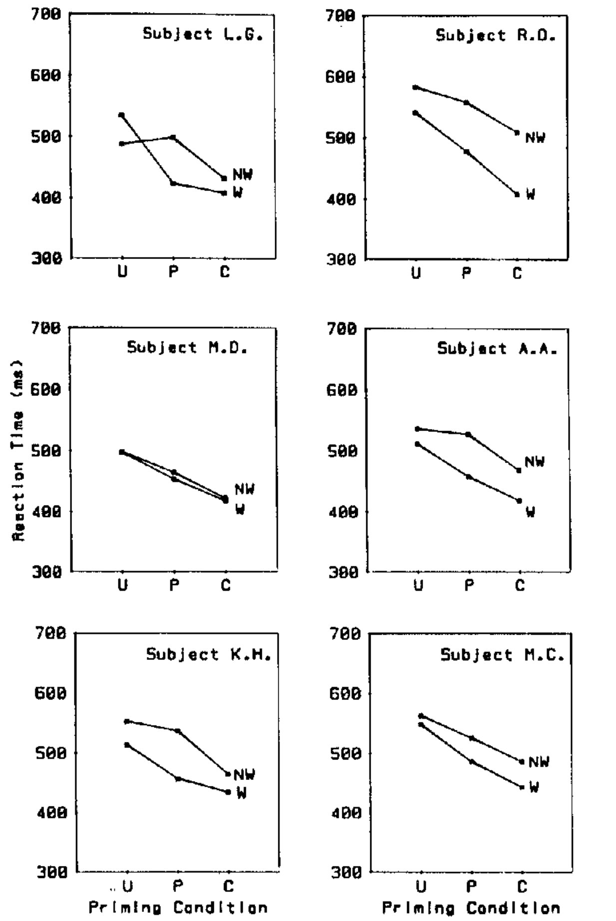

Figure 3. Mean reaction time as a function of priming condition and type of test stimulus for each subject on Day 3 of Experiment 2. (U = unprimed condition; P = partially primed condition; C = completely primed condition; W = word test stimuli; NW = nonword test stimuli.)

Table 7
Goodness-of-Fit Tests for the Mixture Prediction of the Two-State Discrete Activation Models in Experiment 2, on the Basis of Responses to Word Test Stimuli

Day	Mixture parameter (π)	χ^2	*df*
	Subject M.D.		
2	.96	24.5*	11
3	.46	25.6**	10
	Subject A.A.		
2	.70	42.3***	11
3	.35	18.7	11
	Subject L.G.		
2	.22	29.7**	11
3	.02	25.3**	11
	Subject R.D.		
2	.29	30.8**	11
3	.62	45.8***	11
	Subject K.H.		
2	.50	33.2***	11
3	.27	17.0	11
	Subject M.C.		
2	.35	28.0**	10
3	.38	24.5*	11

* $p < .05$. ** $p < .01$. *** $p < .001$.

Discussion

In Experiment 2, subjects learned associations between arbitrarily paired adjectives and subsequently used those associations to enhance their lexical-decision performance in the adaptive priming procedure. Because the pairs were always related, this strategy resulted in large and significant facilitative priming effects. However, there was no evidence of binary reaction-time mixture distributions. Two-state discrete activation models, which assert that node activation is all-or-none, may therefore be rejected again. The results of Experiment 2 verify and extend those of Experiment 1, showing that the two-state activation models are inadequate not only for semantically related prime and test stimuli, but also for episodically related stimuli.

The results from Experiments 1 and 2 are also relevant to a debate concerning the distinction between episodic and semantic memory (cf. McKoon, Ratcliff, & Dell, 1986; Tulving, 1986). Tulving (1972, 1983) has argued that episodic memory for personal events is a system distinct from semantic memory for world knowledge (e.g., lexical information). He has reviewed a large body of evidence supporting such a distinction. On the other hand, McKoon et al. criticized this view and argued that there is only weak empirical evidence supporting the episodic–semantic distinction. They argued that the best evidence for such a distinction would involve factor dissociations, that is, experimental variables that have demonstrably different effects on semantic and episodic memory. McKoon et al. pointed out that there have been few if any reported instances of such dissociations and therefore argued that the distinction between episodic and semantic memory remains unsupported.

The present results, which show no difference in activation dynamics due to semantic (Experiment 1) and episodic (Experiment 2) word associations, are consistent with the unitary view and do not support the episodic–semantic distinction. Of course, there is no reason why the two putative memory systems must have different activation dynamics. This is simply one more instance in which they could have been different and were not.

General Discussion

Two experiments have been reported here to test discrete versus continuous models of memory activation. In Experiment 1, strong facilitative priming effects were produced with semantically associated word pairs, and no evidence of binary mixture distributions was observed, disconfirming the mixture prediction of two-state discrete activation models. In

Experiment 2, episodic prime-test relations were established via paired-associate learning, and large facilitative priming effects were elicited with these episodically related pairs. Again, the mixture prediction of two-state discrete activation models was disconfirmed. Models postulating continuous activation dynamics are supported.

Of course, the present data do not necessarily require an explanation in terms of continuous activation models. Higher order discrete models with three or more different activation states might also explain why the original binary mixture prediction (Equation 1) failed here. For example, three distinct activation states could produce three independent basis distributions just like those found respectively in the unprimed, partially primed, and completely primed conditions of Experiments 1 and 2. The only way to test such a three-state model versus a continuous model using the adaptive priming procedure would be to insert a larger number of different priming intervals so as to obtain at least two different mixtures of the discrete states underlying the basis distributions. Given that there were only three priming intervals in the present experiments, including just one intermediate priming interval, such higher order discrete models cannot be tested on the basis of the present data.

Theoretical Implications

Models of semantic and episodic memory. The results of the present experiments clearly disconfirm models that postulate all-or-none activation growth at nodes in semantic and episodic memory (e.g., Anderson, 1976; Collins & Quillian, 1969; Hayes-Roth, 1977; Quillian, 1968). Of course, this does not mean that all aspects of those models must be rejected. To the extent that discrete activation growth is not an integral property of some model, the model might be judiciously altered so as to account for the results reported here. Anderson (1983a, 1983b), for instance, modified his ACT model in exactly this way. The resulting ACT* model does incorporate a continuous activation process.

Interpretation of temporal priming and speed–accuracy trade-off functions. Given our results, there is now a firmer basis for interpreting temporal priming functions (i.e., plots of priming effects versus length of priming interval; e.g., Warren, 1977) and speed–accuracy trade-off (SAT) functions (e.g., Dosher, 1982). As Meyer et al. (1988) have pointed out, the apparently gradual growth of accuracy and facilitative priming over time could reflect either a continuous accumulation of information or discrete transitions between distinct activation states with stochastic transition times. In the former case, the mapping between activation states and data would be fairly direct, with accuracy or priming effects at a particular moment reflecting an intermediate, graded degree of activation. In the discrete case, however, the mapping would be somewhat more complex: data from any given trial might come from either one of only two discrete activation states. Patterns of mean reaction times, mean reaction time differences, or overall error rates alone cannot distinguish between these two quite different interpretations, even though theorists often adopt the continuous interpretation as a default option (cf. Meyer et al., 1988).

The present results suggest that the continuous interpretation is appropriate for the case of priming in semantic and episodic memory retrieval. However, the results of Meyer et al. (1985) suggest that for the case of simply binary response preparation, a two-state discrete model may be more appropriate.

General issues concerning information processing. Although the present work has focussed on models of activation in semantic and episodic memory, there is a broader context in which the problem of distinguishing between discrete and continuous models can be viewed. The problem concerns how models of information processing in general should characterize the time course of information transmission. Several kinds of discrete models (e.g., Donders, 1868/1969; Falmagne, 1965; Link, 1982; Miller, 1982; Sternberg, 1969; Theios & Smith, 1972) and continuous models (e.g., Eriksen & Schultz, 1979; McClelland, 1979; Turvey, 1973) have been proposed. Our adaptive priming procedure may be applied to test various aspects of these models in an effort to determine when and where discrete state transitions or continuous information accumulation occur. For example, some recent research on response preparation illustrates the potential power of the adaptive priming procedure for investigating other areas beyond memory activation (Meyer et al., 1984, 1985).

Related Findings

Two lines of related findings, when combined with the results of the present experiments, provide further insights concerning the interactions among various components of the information-processing system. These include studies of response preparation using the adaptive priming procedure (Meyer et al., 1984, 1985), and studies of the semantic-memory system using a speed–accuracy decomposition technique (Kounios et al., 1987; Meyer & Irwin, 1981; Meyer et al., 1988).

Studies of response preparation. Using the adaptive priming procedure, Meyer et al. (1984, 1985) found that the preparation of simple binary responses is a discrete, all-or-none process. Their studies involved a highly compatible choice-reaction task in which the priming information was the lexical status of a string of letters. Prime stimuli were presented at various moments before the onset of a test arrow that specified which of two finger-press responses to make. Subjects were told that if the prime stimulus was a word, then the subsequent test arrow would point to the right, requiring a right-finger response. When the prime was a nonword, the test arrow pointed to the left, requiring a left-finger response. Subjects were encouraged to prepare the appropriate response before the test arrow appeared so as to reduce their reaction times.

A principal difference between the current version of the adaptive priming procedure and the previous one is that in Meyer et al. (1984, 1985), subjects used the prime stimuli to prepare a specific response or a subset of possible responses. The lexical status of the prime stimuli completely specified the response that would be required. In contrast, for the present experiments, the prime stimuli provided no information about what response would be required; instead, the

primes activated related nodes in memory, resulting in speeded retrieval of the concepts represented by those nodes.

Corresponding to these procedural differences, there were significant differences in the observed reaction-time data. For situations in which the stimulus-response mapping was relatively simple, the distributions of reaction times obtained by Meyer et al. (1985) ruled out certain classes of models that entail continuous growth of response preparation over time. Instead, the mixture prediction made by two-state discrete models of response preparation fit their data extremely well, unlike what we found here for semantic and episodic priming.[4] Thus, not all components of the information-processing system involve continuous dynamics.

Speed–accuracy decomposition. Other recent work on the dynamics of activation in memory provide converging support for the findings of the present experiments, however. Meyer et al. (1988) and Kounios et al. (1987) have used a speed–accuracy decomposition technique in which the degree of partial information accumulated during a cognitive operation (e.g., sentence verification) can be estimated as a function of time. The procedure involves a mixture of regular reaction-time trials and signal trials. On signal trials, subjects must respond to a test stimulus as quickly as possible after the presentation of an auditory response signal, guessing about the correct response if necessary. Using certain analytical procedures, it is possible to estimate the accuracy of the guessing process, and hence the amount of accumulated partial information, for responses made at various moments in time after the onset of the test stimulus. Results from the speed–accuracy decomposition technique have suggested that information accumulates continuously during word-recognition processes (Meyer et al., 1988) and sentence verification processes (Kounios et al., 1987). Both of these studies ruled out two-state discrete activation models, in agreement with the present findings.

Conclusion

Taken as a whole, the results reviewed above suggest that different parts of the information-processing system have different dynamic properties. In particular, it appears that simple response preparation may be a discrete all-or-none process while memory retrieval is a continuous process. The activation resulting from memory retrieval and other cognitive operations, even while accumulating continuously, may only become available to the response-preparation system in a discrete fashion. That these two subsystems have different dynamic properties suggests that the overall information-processing system may not be characterized by one simple discrete or continuous model. Instead, a more complex hybrid combination of discrete and continuous processes may be required to adequately model the system.

Why two different dynamic principles underlie the operation of memory retrieval and response preparation remains unclear. One possible answer may stem from the nature of response or decision "codes" versus early raw stimulus "features." Perhaps response preparation is sometimes discrete because it involves the specification of just a few parameters relevant to a desired movement, and information must be complete with respect to these parameters before any one of them can be specified (Miller, 1983; Rosenbaum, 1980). In the experiments of Meyer et al. (1985), there were usually just two possible responses to be prepared, so the mapping from the priming information on the response codes was many to few. On the other hand, the accumulation of information in lexical memory may entail a relaxation process among many units with mutually constraining links, as in parallel distributed processing models (cf. Rumelhart & McClelland, 1986). Because the mapping from prime stimuli to test stimuli was many to many in the present experiments, several related nodes in memory may have become partially activated to varying degrees when a prime was presented. An efficient retrieval system might allow for the partial activation of many possible codes when they are all candidates for retrieval, while activating none if there are few possible codes to be retrieved until a criterion degree of disambiguating information is received. We suggest that lexical retrieval may be implemented in the first way (i.e., as a continuous process) and that response preparation may be implemented in the second way (i.e., as a discrete process) when the stimulus–response mapping is simple. Future theoretical and empirical efforts will have to uncover the dynamic properties of other information-processing subsystems and ascertain how these systems interact as they do.

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[4] Recent papers by Eriksen and Schultz (1979) and by Coles, Gratton, Bashore, Eriksen, and Donchin (1985) have suggested that response preparation may be a continuous rather than a discrete process. This conclusion is based on evidence of partial response activation using a response-competition paradigm with both reaction-time and psychophysiological measures. However, although a continuous process should yield partial response activation, the reverse is not necessarily the case: Partial response activation could arise under a discrete model (e.g., see Miller, 1982). We do not believe that evidence for partial response activation damages the conclusion of Meyer et al. (1985) that response activation may be a discrete process when there is a simple stimulus–response mapping.

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